EXHIBIT 55
[FILED UNDER SEAL]

IN THE UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF TEXAS
SHERMAN DIVISION

The State of Texas, et. al., Plaintiffs, vs. Google LLC, Defendant.	Case No: 4:20-cv-00957 Sean D. Jordan

EXPERT SUR-REBUTTAL REPORT OF MICHAEL R. BAYE
October 4, 2024

HIGHLY CONFIDENTIAL
SUBJECT TO PROTECTIVE ORDER

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I. INTRODUCTION

1) I have been retained by counsel for Google to provide expert analysis and opinions in this case. As part of my assignment, I submitted an expert report on August 6, 2024 ("Baye First Report") that responded to opinions in the opening report of Plaintiff States' expert Professor Joshua Gans of June 7, 2024 ("Gans Opening Report"). On September 9, 2024, Plaintiff States submitted the Rebuttal Report of Joshua Gans ("Gans Rebuttal Report"). I have been asked by counsel for Google to respond to certain opinions contained in Professor Gans' Rebuttal Report in this sur-rebuttal report.[1] This report is narrowly focused on those opinions, and that focus should not be construed as an endorsement of any other opinions expressed in Professor Gans' Opening or Rebuttal Reports that I do not discuss here. A list of the materials I relied upon in this report is attached as Appendix A. Figures not included as Exhibits in the text are attached as Appendix B.

II. PROFESSOR GANS' NEW AD EXCHANGE MARKET POWER OPINIONS

2) Professor Gans' Rebuttal Report includes a new methodology for calculating market shares in his narrow candidate market for ad exchanges for open web display ads in the United States.[2] In his Opening Report, Professor Gans used Google's internal Header Bidding Monitor data to calculate Google's share of his candidate ad exchange market.[3] The Header Bidding Monitor data include information about impressions occurring on about fifty different ad exchanges. In my August 6, 2024 First Report, I identified methodological flaws in Professor

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[1] Gans Rebuttal Report, at ¶¶119-124, 132, 514, 515, Tables 4, 5, 11-14; ¶¶169-171, 517, Figures 2-4, 30, 31; ¶¶236-238, Figures 10-12; ¶¶318-319, Figures 16, 40; ¶¶346-347, Figures 17-20; ¶¶421-423, 429-432, Figure 23, Table 8.

[2] Gans Rebuttal Report, at ¶¶233, 235-238, Figures 10-12. Professor Gans says, "In my Opening Report, I presented a conservative calculation of AdX's market share between 2018 and 2021 based on all DFP indirect transactions and empirical evidence on AdX's share of impressions transacted outside of DFP. … [In this section,] I focus on the conclusions Professor Baye would have reached had he done a proper market share calculation with the dataset he compiled of third-party exchange transactions based on productions by these exchanges." (Gans Rebuttal Report, at ¶¶233-235).

[3] Expert Report of Joshua Gans, June 7, 2024 ("Gans Opening Report"), at Table 5, fn. 428. ("Data sourced from Header Bidding Monitor dataset described in 2023/04/17 Transmittal Letter re Data Production.").

Gans' calculations and demonstrated how, after correcting for those flaws, Professor Gans' methodology generated significantly lower shares for Google in his candidate ad exchange market.[4] In his Rebuttal Report, Professor Gans calculates shares in his candidate ad exchange market using a wholly new and distinct methodology and entirely different data than he used to calculate Google's share of that market in his Opening Report.[5] Professor Gans also uses different criteria for measuring impressions in his candidate market than he utilized in his Opening Report.[6]

3) When calculating the market share of Google's ad exchange (AdX) based on matched impressions (as Professor Gans purports to do in both of his reports[7]), a proper methodology would divide the number of matched impressions transacted through AdX during a particular time period (the "numerator") by the total number of matched impressions transacted through all ad exchanges during that same time period (the "denominator").

[4] Expert Report of Michael R. Baye, August 6, 2024 ("Baye First Report"), at ¶¶320-326, Exhibit 20. ("By merely correcting Professor Gans' calculations to appropriately account for the full volume of ad impressions transacted on rival ad exchanges, I find that Google's share in his narrow candidate ad exchange market is modest.").

[5] Gans Rebuttal Report, at ¶¶236-238, Figures 10-12. I note that Professor Gans' new methodology for calculating AdX's share in his candidate ad exchange market does not account for repositioning (e.g., firms like Freewheel expanding its offerings to include Professor Gans' narrow definition of display ads), low barriers to entry (which can also be observed through distribution of ad exchange volumes I show in Figure 1), and extensive multi-homing by publishers and advertisers across ad exchanges. The corrections that I make in this section to Professor Gans' new AdX share calculation do not address these economic reasons why Google lacks monopoly power. As a result, such calculations continue to overstate AdX's actual market power for the same reasons I have already discussed in the Baye First Report.

[6] The ad exchange shares in Professor Gans' Opening Report were based on worldwide user impressions transacted by North American publishers, while his new market share is based on U.S. user impressions transacted by publishers worldwide. Professor Gans states that "[t]he geography of this dataset is restricted to North America." (Gans Opening Report, at Table 5, fn. 428). A production letter that Professor Gans also cites to explains further that region in these data is defined as the "[r]egion on which the Google sales team managing the account focuses." ("2023.04.17 Transmittal Letter re Data Production," (April 17, 2023)). In his Rebuttal Report, Professor Gans states that his new market share calculation includes third party data filtered to "limit to impressions from the United States where applicable." (Gans Rebuttal Report, at Figure 10, fn. 398). Professor Gans also changes the ad formats that he utilizes to compute his market shares. For example, Professor Gans' Opening Report ad exchange market share included video ads, while his new market share excludes video ads. In his Opening Report, Professor Gans states that "video ads are not taken into consideration" for his original AdX market share calculations. (Gans Opening Report, at Table 5, fn. 428). In his Rebuttal Report Analysis, Professor Gans excludes video impressions using the field 'creative_ad_format'. (Gans Rebuttal Report Backup Materials, folder "Third Party Ad Exchange Market Share Analysis").

[7] Gans Opening Report, at Table 5, fn. 428 ("To calculate the AdX share, the AdX matched impressions as defined here are summed and divided by the sum of the total matched impressions for each year."); Gans Rebuttal Report, at ¶236; Gans Rebuttal Report Backup Materials, folder "Third Party Ad Exchange Market Share Analysis".

4) While Professor Gans appears to have correctly limited the impressions in the numerator of his new market share calculations in his Rebuttal Report (i.e., correctly excluding the Open Bidding impressions that he attributed to AdX in his Opening Report)[8], the denominator in his calculations understates the total number of impressions transacted by all ad exchanges and, as a result, produces an inflated AdX market share. More concretely, Professor Gans' denominator is merely the sum of impressions across only nine ad exchanges[9] that submitted data into the record, which means that he entirely ignores the roughly forty other ad exchanges from the Header Bidding Monitor data that he included in his ad exchange market share calculation in his Opening Report.[10]

5) As I explain in more detail below, simply accounting for the volume of impressions transacted via the ad exchanges that Professor Gans omits from the denominator of his Rebuttal Report Figure 10 reduces his estimate of AdX's market share by nearly [redacted] percentage points to [redacted] percent.[11] Exhibit 1 presents these results.

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[8] Gans Rebuttal Report Backup Materials, folder "Third Party Ad Exchange Market Share Analysis"; *See also* Baye First Report ¶321, fn. 462.

[9] [redacted]

[10] Gans Opening Report, at Table 5.

[11] As I show below, under conservative assumptions, Professor Gans' AdX market shares are actually no more than [redacted] percent. To do so, one need only include header bidding volume indicated as "Unknown" and the volume of other indirectly sold ads in proportion to the size of the exchanges that Professor Gans excludes and apply Professor Gans' assumptions about the volume of ads transacted by these exchanges outside of DFP.

Exhibit 1

[redacted]

6) As indicated above and in the Baye First Report, Google's data show approximately fifty ad exchanges that transacted impressions in Professor Gans' narrow candidate ad exchange market.[12] My calculations underlying Exhibit 1 include in the denominator only impression

[12] *See* Figure 1 for additional detail on ad exchanges that Professor Gans excluded, and I have included in the market share calculations in Exhibit 1. I refer to the number of ad exchanges in the data as an approximate number for at least two reasons. First, my analysis combines some exchanges in the raw data where they are owned by the same parent. I provide this mapping in the backup of this report. Second, as I noted in the Baye First Report, new exchanges enter the data over time and, during any particular period of time, some exchanges may show up or disappear from a particular data view depending upon how the data are filtered (e.g., the types of ads they transact or the way in which they are transacted). Thus, the total number of exchanges that have transacted any kind of display ad at a particular period of time may differ from the number of exchanges observed

volumes that can be attributed to a particular third-party ad exchange by the name specified in the data. This is a fraction of the overall impression volumes for third-party ad exchanges.[13] Therefore the denominator of the market shares in Exhibit 1 understates the actual volume of impressions transacted by these exchanges inside Professor Gans' narrow candidate market for ad exchanges for display ads and, consequently, overstates AdX's market share. There are at least three reasons why that is so:

a. **Unattributed volumes on DFP.** Certain subsets of Google data can be attributed to matched impressions transacted by third-party ad exchanges, generally, but lack the precise name of the ad exchange.[14] For example, while Google data indicate the name of the winning ad exchange for all Open Bidding transactions, some header bidding transactions indicate "Unknown" for the ad exchange. By definition, none of the matched impressions for these "Unknown" header bidders transacted on AdX, and it is highly likely that a substantial share of those matched impressions were, in fact, transacted by the ad exchanges that Professor Gans ignored in his market share calculation and did not submit data into the record. However, because

transacting a narrow type of ad at a given moment in time. [redacted]

[13] In these corrections, I obtain data on Open Bidding impression volumes for the ad exchanges that Professor Gans excluded from the same data source that he uses to calculate AdX impressions in his Rebuttal Report market shares: MDL RFP 243 AdX. I obtain header bidding impression volumes from MDL RFP 243 DFP Reservations which contains information about other remnant indirect ad sales by DFP publishers and can also be limited by ad types, geography, and other dimensions in the same way as Professor Gans' AdX data are limited.

[14] Professor Gans describes this in relation to Google's efforts to develop better header bidding detection. Professor Gans states that "until 2018, [Google] did not have a reliable process to identify impressions transacted by exchanges conducting Header Bidding," citing to a production letter that states "both the degeneracy condition and the key name condition may fail to identify some instances of header bidding (e.g., when fewer than 70 line items are used, when a firm unknown to Google employs header bidding)[.]" (Gans Rebuttal Report, at ¶451, fn. 774; "2023.04.17 Transmittal Letter re Data Production," (April 17, 2023)).

my correction to Professor Gans' market shares in Exhibit 1 only utilizes Google data when I could identify the name of the specific exchange, my correction does not account for any portion of these "Unknown" header bidding ad exchange impressions. Including these matched impressions from third-party ad exchanges that were served on DFP in the denominator would reduce Google's market share.

b. **Unattributed volumes on third-party ad servers.** The denominator in my correction in Exhibit 1 assumes that all (100 percent) of the impressions of third-party exchanges that did not submit data into the record were served by DFP (i.e., that these third-party exchanges did not transact any impressions other than those served by DFP).[15] In fact, impressions transacted through third-party exchanges may be served in several other ways, including by (i) any of the dozens of third-party ad servers available to publishers,[16] (ii) in-house ad servers,[17] (iii) without use of an ad server through direct calling of an ad exchange,[18] or (iv) through header

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[15] I make this assumption purely to eliminate any possibility that I am somehow "double-counting" impressions. As a result, the approach I use here adopts the exact same assumption that Professor Gans employed in Table 5 of his Opening Report—that is, I assume that all (100 percent) of matched ad impressions transacted by third-party ad exchanges that did not produce data in the record are served by DFP. Therefore, the denominator in my calculations does not include any matched impression transacted by the dozens of third-party ad exchanges that did not submit data into the record that was served on any of the many alternatives to DFP.

In his Rebuttal Report, Professor Gans asserts that he "accounted for the small minority of impressions that may have been served by non-Google ad servers as explained in footnote 430 of [his] Opening Report." (Gans Rebuttal Report, at ¶448). Professor Gans' statement is not correct. Although Footnote 430 of Professor Gans' Opening Report discusses his efforts to "bound the effect" of his use of DFP-only data, the market shares he presents in his Rebuttal Report do *not* account for the volume of matched impressions transacted on third-party exchanges that are served on non-Google ad servers.

[16] *See, e.g.,* Baye First Report, at Figure 10.

[17] *See, e.g.,* Baye First Report, at ¶237, fn. 305, ¶243.

[18] As I indicated in the Baye First Report, the documents that Professor Gans utilized for his ad server market shares describe this as one option used by publishers. (*See* Baye First Report, at ¶330). Third-party ad exchanges describe implementation of ad tags on publisher websites to directly query the exchange for ads. For example, the Sovrn ad exchange explains how to obtain ads directly on a website built with WordPress: "Follow these steps to properly install your Sovrn ad tags on your WordPress website. Please note that if the code is not installed correctly, the ads will not appear… 1. Navigate to Widget… 2. Locate the Text widget… 3. Insert your Sovrn ad tag code… 4. You're done! Once the code is properly placed, you should see a Sovrn house ad. Please allow up to 48 hours for an ad to begin serving." (Sovrn, "How to Install Sovrn Ad Tags on a WordPress Site,"

bidding run without an ad server.[19] If the [redacted] document that Professor Gans relies upon is correct and DFP served no more than [redacted] percent of the impressions in his candidate market for ad servers,[20] then these other methods of serving ads would represent at least [redacted] percent of impressions.[21] Including the portion of impressions from third-party ad exchanges that were not served by DFP in the denominator would reduce Google's market share.

c. **Third-party ad exchanges not identified in DFP data.** The denominator used to construct Exhibit 1 does not exhaustively account for the volume of impressions from all known competitors in Professor Gans' narrow candidate market for ad exchanges. While Google's transaction data identify about fifty ad exchanges,[22] other evidence shows that there are actually many more ad exchanges operating in Professor Gans' candidate market. For instance, advertisers can use Google's DSP

available at: https://www.sovrn.com/blog/install-ad-tags-wordpress-site/. Accessed September 17, 2024). These instructions also appear in the general instructions for setting up ad tags with Sovrn. (Sovrn, "Ad Tags in Ad Exchange," available at: https://knowledge.sovrn.com/kb/ad-tags-in-ad-exchange. Accessed September 17, 2024).

[19] *See, e.g.,* Prebid, "Running Prebid.js without an ad server," available at: https://docs.prebid.org/dev-docs/examples/no-adserver.html. Accessed September 13, 2024.

[20] Professor Gans indicates in his Opening Report that "[a]n internal document from [redacted] shows that DFP served [redacted]% of web impressions in 2017, and they expected it to be [redacted]% in 2022." (Gans Opening Report, at ¶353). *See also* [redacted]. This is the only information about ad server shares that Professor Gans identifies in his Opening Report that is based on impressions. (As I note in the Baye First Report, the share that Professor Gans attributes to 2008 is not, in fact, based on impressions.)

[21] In other words, using a DFP share of [redacted] percent, one could estimate that the true total volume of ads transacted by the third-party ad exchanges that Professor Gans ignores as equal to the volume of their ads served on DFP multiplied by [redacted] If one were to add that volume to the denominator (i.e., increase the base by [redacted] percent) in my market share calculation, it will lead to even lower Google market shares.

[22] As I demonstrated in the Baye First Report, there are several different data sources that Google submitted into production showing the numerous ad exchanges that compete with AdX. The data source that Professor Gans uses to calculate the numerator of his market share (MDL RFP 243 AdX) also provides data on ad exchanges competing in Open Bidding. The data source that identifies third-party exchange volume through header bidding that is most similar to MDL RFP 243 AdX in terms of fields available to apply Professor Gans' filters for ad types and geographic area is the MDL RFP 243 DFP Reservations Data. Therefore, to correct Professor Gans' new AdX shares, I use MDL RFP 243 DFP Reservations Data to obtain header bidding volumes for third-party exchanges that Professor Gans excluded from his new market shares.

to bid into more than 100 ad exchanges.[23] In addition, the open source Prebid platform for header bidding provides access to "bidder adapters" that support over 300 SSPs and ad exchanges.[24] Including the matched impressions for the remaining competitors not identified in Google data in the denominator would reduce Google's market share.

7) Using available information and standard economic techniques to approximate (a) unattributed volumes on DFP[25] and (b) unattributed volumes on third-party ad servers[26]—in addition to the corrections based on directly observed data in Exhibit 1—results in a market share of [redacted] percent.[27]

8) It is my opinion that the [redacted] percent AdX share resulting from these two adjustments to Exhibit 1 more accurately reflects Google's market share in Professor Gans' candidate ad

[23] *See, e.g.,* Google, "Supported display exchanges - Display & Video 360 Help," available at: https://support.google.com/displayvideo/table/3267029. Accessed September 16, 2024. DV360 identifies display, native, and audio & video exchanges. Some companies are listed with more than one exchange and some exchanges are indicated as "via Bidswitch." Bidswitch is ad tech offered by Criteo and indicates that it "provides the underlying infrastructure that normalizes the connections between different programmatic technology platforms (Most commonly DSPs and SSPs). Today, we facilitate more than 4,000 of these different connections globally, providing an integral infrastructure to support programmatic players at all tiers and levels of the industry." (Bidswitch, "Technology - A smart infrastructure for programmatic platforms," available at: https://www.bidswitch.com/technology/. Accessed September 24, 2024).

[24] *See, e.g.,* Prebid, "What is Prebid.js?" available at: https://docs.prebid.org/prebid/prebidjs.html. Accessed September 16, 2024.

[25] I approximate this by allocating proportional amounts of the "unknown" ad exchange header bidding impressions and other indirect impressions to these other ad exchanges that are named in Google data.

Because I do not attribute the entirety of the "unknown" impressions to the "other" 40 exchanges that Professor Gans excludes, I avoid the possibility that the impressions I include might be double-counted with the impressions of exchanges that did submit data into the record.

[26] I estimate the volume of impressions from these exchanges that are served outside of DFP assuming an 80 percent DFP market share. This implies that the volumes of impressions found in DFP are, on average, [redacted] percent of the overall (complete) volume of third-party ad exchanges. Therefore, a reasonable approximation of the overall volume of the 40 ad exchanges that Professor Gans excludes from his shares, but appear in DFP data, is [redacted] times the volume obtained inside DFP.

[27] *See* Figure 2. In addition to the corrections I implement above [redacted] I include an estimate of the portion of "Unknown" ad exchange header bidding impressions and other indirectly sold impressions attributable to the exchanges Professor Gans and apply a DFP share of [redacted] percent to these ad exchanges.

exchange market for his narrow definition of open web display impressions than Professor Gans' estimates (based on his new methodology).[28] However, even the [redacted] percent estimate likely overstates AdX's share in Professor Gans' candidate ad exchange market because my approximation of additional third-party exchange volumes accounts for exchanges that participate in header bidding on DFP *but does not account* for other indirectly sold ads in Professor Gans' ad exchange market (i.e., point (c) above).[29] Consequently, these estimates assume that strictly less than [redacted] percent of impressions transacted by all third-party are not served on DFP.[30] If, instead, one assumed that [redacted] percent of *all* indirectly sold ads were served on third-party ad servers or without an ad server, then the calculations that Professor Gans presents in his Rebuttal Report Figure 20 would imply that AdX's share of his candidate U.S. ad exchange market was no more than [redacted] percent in each month from April 2019 through May 2020.[31] Expressed differently, if just

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[28] Figure 2 shows how the AdX market share varies over time. I use January 2019 through May 2021 because some third-party ad exchanges' data are not available outside of this window. [redacted]

[29] Even if one employs the assumption that only [redacted] percent of impressions are served by in-house ad servers, third-party ad servers, direct calls, and header bidding without an ad server, this would mean that the corrections described above still have not addressed an additional [redacted] indirect ad impressions that are not attributable to AdX. By comparison, Professor Gans calculates that AdX transacted almost [redacted] impressions over the 14 months covered by his market shares. These unaddressed indirect impressions are not part of my corrected market share calculations, and including them in the ad exchange market share denominator would further reduce AdX's share.

[30] My methodology is conservative for two reasons: (i) [redacted]

[31] *See* Figure 3. Professor Gans' Rebuttal Report Figure 20 is entitled "AdX share of all DFP indirect transactions (worldwide)." In his calculations, Professor Gans does not limit the data to U.S. users nor publishers, further, he makes no effort to limit the data to his candidate market beyond filtering "[t]he column 'is_mobile_app_request' … to be 'False' and the column 'is_youtube_inventory' … to be 'False.' … Impressions are via AdX if the column 'transaction_type' has the value '0' or '4,' which represents 'Open auction' and 'First Look deals.'" (*See* Gans Rebuttal Report, at Figure 20, fn. 604). Additionally, in the footnote to Figure 20, Professor Gans claims that "[a]ll impressions other than direct deal ones are indirect" and uses this definition to define the denominator of his AdX share of all DFP indirect transactions. (*See* Gans Rebuttal Report, at Figure 20,

[redacted] percent of all indirect ad impressions were served by in-house ad servers, third-party ad servers, direct calls, and header bidding without an ad server (so that there is no double-counting), then Professor Gans' calculations indicate that AdX's share was no more than [redacted] percent during the time period he analyzes.

III. PROFESSOR GANS' NEW SSNIP ANALYSES AND RELATED CALCULATIONS FOR HIS SMALL ADVERTISER BUYING TOOLS CANDIDATE MARKET

A. Professor Gans' New Buying Tool SSNIP Analysis

9) Professor Gans provides new opinions about the profitability of a "small but significant and non-transitory increase in price" ("SSNIP") in his candidate market for small advertiser ad buying tools. In his Opening Report, Professor Gans asserts that a hypothetical monopolist test ("HMT") "reveals that ad-buying tools for small advertis[ers] for buying open web display advertising via open auction is a relevant product market."[32] However, he provided no analyses or documentary evidence in support of this assertion. Professor Gans makes new claims to support this point in his Rebuttal Report Figures 2 and 3, arguing that internal Google documents show that Google could profitably increase prices by over [redacted] percent.[33] Based on this, Professor Gans erroneously concludes that these documents indicate that a hypothetical monopolist could profitably increase prices in his candidate market for small advertiser ad buying tools.

fn. 604). Using DOJ RFP 57 DRX Internal Stats Data, I recalculate this share in the context of a DFP ad server share of 80 percent by utilizing his code and making the following adjustments: limit the observations to publishers in the United States, remove from the denominator impressions associated to AdX Direct, (using gfp_network_id = -1 and AuctionInventorySource as described in GOOG-AT-MDL-009777293) and multiply the volume of DFP indirect transactions by 1.25 [=100/80] to calculate the denominator. I note that the data on which Professor Gans relies for his Rebuttal Report Figure 20 does not allow one to limit based on the location of users.

32 Gans Opening Report, at Section IV.E.2.

33 "However, Google actually conducted its own HMT experiment in 2014. Google increased the take rate for display ads on Google Ads by [redacted] Google measured higher profits and Google never lowered the rate back to [redacted]." (Gans Rebuttal Report, at ¶169); "Google conducted another HMT experiment in 2018. In a simulation, Google increased Google Ads' margin on AdX from 15% to [redacted]%. Despite increasing its take rate by more than [redacted]%, Google observed an overall increase in profit of [redacted]%." (Gans Rebuttal Report, at ¶170).

10) The price increases Professor Gans points to in these documents do not amount to a SSNIP in the candidate market for small advertiser ad buying tools that he defined in his Opening Report. First, Professor Gans has not examined whether the Google Ads margin was at, above, or below competitive prices at the time that Google contemplated the strategies described in these documents.[34] Second, Professor Gans has not demonstrated that these documents pertain to the use of tools to purchase ads in his narrow market.[35]

11) More broadly, Professor Gans' conclusion that the document he relies upon indicates a SSNIP was profitable because Google might have been able to increase its profits through a "price increase" is not a valid approach to defining a relevant market. Firms routinely raise prices in response to increases in demand, increases in cost, increases in quality, and a host of other factors that are unrelated to monopoly power. Taken to its logical conclusion, Professor Gans' approach would mean that any business that analyzes whether it would be profitable to increase prices and suggests that the answer is "yes" is a monopolist in a relevant antitrust market. These documents are therefore unreliable for determining whether a SSNIP would be profitable in Professor Gans' narrow candidate market for small advertiser ad buying tools.

12) The document Professor Gans relies on in his Rebuttal Report Figure 2 fails to support Professor Gans' opinion that there is a distinct market for small advertiser ad buying tools; the document *is* consistent with my view that Google competes as an integrated, multi-sided platform

[34] *See, e.g.,* Department of Justice & Federal Trade Commission, *Merger Guidelines*, 2023, at section 4.3.B.

[35] More specifically, Professor Gans does not demonstrate that these documents analyze changes for his narrow definition of small advertiser buying tools for open "web display advertising via open auction" in the U.S. (Gans Opening Report, at Section IV.E.2).

that takes into account how changes on the advertiser side impact publishers using AdX and DFP.[36] While this document considers a proposal to increase the Google Ads margin by [redacted] percentage point from [redacted] percent to [redacted] percent,[37] it does not consider the impact on advertisers in isolation. At the time this document was drafted in 2014, Google had recently implemented Project Bernanke and would soon implement Global Bernanke.[38] The document explicitly notes that Google expected a "small drop in GDN win rate (mitigated by DRS/ Bernanke)."[39] As I explained in the Baye First Report, documents indicate that Bernanke increased the size of the pie and benefited both publishers and advertisers, such that even with an increase in the margin from [redacted] to [redacted] percent, advertisers and publishers would have both been better off.[40]

13) The document Professor Gans uses for his Rebuttal Report Figure 3 is also inconsistent with his opinion that there is a distinct market for small advertiser ad buying tools; it *is* consistent with my view that Google competes as an integrated, multi-sided platform that takes into account how changes on the advertiser side impact publishers using AdX and DFP.[41] Specifically, the document appears to indicate that Google's decision calculus considered the impact of raising its Google Ads margin on the payouts publishers receive.[42] While the document

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[36] *See* GOOG-DOJ-AT-00569936. In addition to the financial impact on Google (e.g., change in profit margin and revenue), the document evaluates the effect on publisher payout and GDN win rate or impressions. (GOOG-DOJ-AT-00569936, at -936).

[37] The document considers the effects of "[i]ncreas[ing the] GDN margin on AdX from [redacted]% to [redacted]%." (Gans Rebuttal Report, at Figure 2).

[38] The document is dated March 2014. GOOG-DOJ-AT-00569936, at -936. "Project Bernanke was launched in November 2013." (GOOG-AT-MDL-008842383, at -385). "Global Bernanke … was an update of Project Bernanke that launched in August 2015." (GOOG-AT-MDL-008842383, at -385).

[39] GOOG-DOJ-AT-00569936, at -936.

[40] Baye First Report, at ¶¶614-616 ("Google assessed that Bernanke was responsible for increasing its advertisers' win rate by [redacted] percent;" "Prior to the launch, studies predicted that Bernanke would increase publisher revenue by between [redacted] and [redacted] percent.").

[41] *See* GOOG-NE-04732984.

[42] *See* GOOG-NE-04732984, at -985. Table 1 of this document shows the effect to publisher payout of altering Google Ads' margin.

indicates that simulations suggested that increasing the Google Ads margin from [redacted] to [redacted] percent might increase Google's receipts from advertisers by [redacted] percent, it would decrease publisher payouts by [redacted] percent.[43] Professor Gans provides no evidence that Google chose to implement this margin increase and no explanation for why Google would choose not to implement a profitable price increase. Moreover, Professor Gans' analysis in Rebuttal Report Figure 30 indicates that, between January 2020 and March 2023, the Google Ads margin on ad spend through AdX declined to [redacted] percent.[44] This decline in the Google Ads margin (which occurred after the analysis cited by Professor Gans indicated that an increase would be profitable) suggests that Google faces competitive constraints beyond those included in Professor Gans' standalone small advertiser ad buying tools market. This body of evidence is instead more consistent with his "SSNIP" being unprofitable in a multi-sided market.

B. Professor Gans' New Buying Tool Price Discrimination Analyses

14) Professor Gans also offers new opinions that his narrow candidate market for small advertiser ad buying tools is supported because of "price discrimination between different ad formats, making them separate markets,"[45] and purports to have demonstrated price discrimination through analysis of margins across types of ads and tools for transacting ads.[46] In his Opening Report, Professor Gans mentions price discrimination only once in relation to his discussion of the

[43] GOOG-NE-04732984, at -985.

[44] According to Professor Gans' backup materials for his Rebuttal Report Figure 30, the integrated Google take rate for display ads bought on Google Ads through AdX was [redacted] percent between January 2020 and March 2023. Based on his assumed AdX take rate of 20 percent, this means that the Google Ads margin was [redacted] percent [redacted] While Professor Gans' Rebuttal Report indicates that Figure 30 goes through March 2024, review of the backup indicates that his data only go through March 2023. *See* Gans Rebuttal Report Backup Materials, at file "Take Rates by Transaction Types.xlsx", tab named "DV360_GA_Take rate", cell D3.

[45] Gans Rebuttal Report, at ¶517.

[46] "Because the AdX take rate is approximately constant at 20%, the figure shows price discrimination on the Google Ads take rates." (Gans Rebuttal Report, at ¶171).

"principles of market definition," broadly.[47] However, in his Rebuttal Report, Professor Gans provides new analyses in Figures 4,[48] 30, and 31 which purportedly demonstrate that "Google price discriminates on Google Ads and DV360 across ad formats."[49]

15) As an initial matter, the new analyses in Professor Gans' Rebuttal Report Figures 4, 30, and 31 do not establish price discrimination inside or outside either of his candidate ad buying tool markets. Professor Gans' analyses of ad buying tool margins does not characterize price discrimination as the term appears in economics literature. For example, in our textbook *Managerial Economics & Business Strategy*, Professor Prince and I indicate that price discrimination is "[t]he practice of charging different prices to consumers for the same good or service."[50] The fact that different types of ads—or more generally, different types of products—

[47] "Smaller markets can be appropriate when price discrimination between types of customers is possible." (Gans Opening Report, at ¶126). Professor Gans' Opening Report offers no quantitative or other evidence that firms inside or outside his small advertiser ad buying tool candidate market engage in price discrimination. To the extent that Professor Gans describes pricing in his candidate buying tool market, it is only to observe qualitatively, that there are four small advertiser buying tools that charge advertisers on a CPC basis, which may or may not variously also offer CPM or CPV payment models. Professor Gans asserts that small advertiser buying tools "often charge advertisers based on the 'media cost' of the inventory purchased, which can be charged in different ways, such as cost-per-click (CPC), cost-per-thousand impressions (CPM), cost-per-view (CPV), cost-per-action (CPA), or on a pay-per-sales model (CPS)." (Gans Opening Report, at ¶235). *See also* Gans Opening Report, at Table 3.

[48] Professor Gans states that his Rebuttal Report Figure 4 represents "[t]ake rates for display ad formats." (Gans Rebuttal Report, at Figure 4). Based on review of his backup, Figure 4 actually shows results of his analysis of video ad formats. One can directly see this by noting that Gans Rebuttal Report Figure 4 is identical to his Figure 31. The title of his Figure 31 indicates the correct ad format based on the backup materials (video ad formats), while his Figure 4 has the incorrect title (display ad formats).

[49] Gans Rebuttal Report, at ¶171.

[50] Michael R. Baye and Jeffrey T. Prince, *Managerial Economics and Business Strategy*, 10th Edition, McGraw-Hill, 2021, at p. 352.

might sell at different prices does not equate to price discrimination.[51] Nor does it imply they are in different relevant product markets.[52]

16) Professor Gans has not shown that Google Ads or any other ad tech company charges different advertisers different prices for using a given tool (e.g., Google Ads) in the same way.[53] Professor Gans' Rebuttal Report Figures 4, 30, and 31 show Google's *overall margin* across the entire ad tech stack, not the price it charges advertisers using its Google Ads or DV360 buying tools.[54] Nor does Professor Gans demonstrate that Google Ads earns different margins from different advertisers buying his narrow definition of display ads. At most, Professor Gans shows that Google's *integrated* margin can be higher or lower for different types of ads or ways of buying ads.[55]

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[51] Variation in prices does not equate to price discrimination. Charging different prices due to differences in costs is not price discrimination. "Price discrimination exists when prices vary across customer segments in a manner that cannot be entirely explained by variations in marginal cost." (Lars Stole, "Price Discrimination and Competition," in *Handbook of Industrial Organization Volume 3*, ed. Mark Armstrong and Robert Porter, 2007, at p. 2224).

[52] It is often the case that different types of products are in the same relevant antitrust market, even though those products might sell at different prices.

For example, charging different prices for different styles of shoes is not price discrimination. If consumers value one style more highly than another, or one style is more costly to produce than another, shoe prices will vary; but this is not price discrimination.

As another example, different grades of gasoline and diesel sell at different prices at the same retail outlet as well as across outlets even when owned by the same company, yet for certain antitrust issues, they have been deemed to be in the same relevant markets. The FTC's complaint filed against Marathon Petroleum Corp's acquisition of Express Mart indicated that the "[r]elevant product markets in which to analyze the effects of the Acquisition are the retail sale of gasoline and the retail sale of diesel." In the Matter of Marathon Petroleum Corporation, Trade Reg. Rep. P 17906 (C.C.H.), 2018 WL 5840959 (Oct. 25, 2018).

[53] Of course, different advertisers may value different types of ads differently and, therefore, use the tools to bid on ads that may be more or less expensive. But, this does not amount to Google engaging in price discrimination.

[54] In describing Rebuttal Report Figure 4, Professor Gans claims that "[b]ecause the AdX take rate is approximately constant at 20%, the figure shows price discrimination on the Google Ads take rates." (Gans Rebuttal Report, at ¶171). However, the 20 percent AdX take rate applies to impressions transacted via open auction. (*See, e.g.,* Baye First Report, at Figure 50). Professor Gans' analysis mixes open auction with programmatic guaranteed and other transaction types that have different AdX margins. That is, the integrated margin he shows for DV360 includes a blend of different AdX revenue shares. Therefore, the premise upon which he states that these calculations are able to show price discrimination is incorrect. As noted earlier, Professor Gans did not consider the Google Ads take rate as the relevant price in his Opening Report.

[55] Professor Gans does not cite to any literature that supports delineating relevant markets according to the margins earned by one firm.

17) Professor Gans' margin analysis also does not support his conclusion that "take rates show a strong segmentation"[56] between the types of ads he includes in his narrow candidate market and the types of ads he excludes.[57] To the extent he shows segmentation, such segmentation is present *within* his narrow candidate market[58] and this segmentation is on the order of the segmentation he finds between ads inside and outside his candidate market.[59] Regardless of the difference in margins across the types of ads and tools he analyzes, it is not unusual for different products within a single antitrust market to have differing prices or margins depending on their cost of production or return on investment. Therefore, it would also be inappropriate as a matter of economics to conclude that advertisers cannot or would not substitute among these options if advertisers' return on investment for one type of ad (or way of buying an ad) became relatively more attractive than its return on investment from another type of ad (or way of buying an ad).

18) Even if one views Professor Gans' analyses of Google Ads margins in his Rebuttal Report Figures 4, 30 and 31 as demonstrating price discrimination, which they do not, Professor Gans' conclusion that "a certain level of price discrimination between different ad formats, mak[es] them separate markets"[60] is unsupported. Professor Gans has failed to conduct an HMT

[56] Gans Rebuttal Report, at ¶517.

[57] At least three groups that Professor Gans identifies in the Gans Rebuttal Report at Figure 30 and Figure 31 (Ad Exchange/Ad Exchange, Ad Exchange/Ad Exchange Video, and 3PE/Non-Google Inventory) relate to ad inventory within his narrow candidate market. Professor Gans does not differentiate between instream and outstream video ads in his analysis.

[58] Professor Gans' analysis shows variation in margins across the groups that comprise his narrow market. For example, in Figure 30, the difference in Google Ads' margin between "Ad Exchange/Ad Exchange" and "3PE/Non-Google Inventory" is [redacted] percent.

[59] Professor Gans' analysis finds that the margins on ads he excludes from his candidate market are comparable to the margins of ads he includes. For example, he calculates a margin of [redacted] percent for AdMob/AdMob (which pertains to mobile in-app inventory that Professor Gans excludes from his candidate market) and a margin of [redacted] percent for 3PE/Non-Google Inventory. The difference between this one category outside his candidate market and another inside his candidate market is smaller than the differences in margins he calculates across the categories of ads entirely within his candidate market.

[60] Gans Rebuttal Report, at ¶517.

in any price discrimination market, and the mere ability to price discriminate does not imply that different ad formats are in distinct antitrust markets.

IV. PROFESSOR GANS' NEW ANALYSES FOR HIS PUBLISHER AD SERVER CANDIDATE MARKET

A. Professor Gans' New Ad Server SSNIP Analysis

19) In his Opening Report, Professor Gans asserted that an HMT "reveals that publisher ad servers used for the sale of open web display advertising is a relevant product market,"[61] but he provided no analyses or documentary evidence in support of that assertion.[62] Professor Gans' Rebuttal Report contains new analysis that he interprets as showing that Google could impose a SSNIP on customers in his narrow candidate market for publisher ad servers.[63]

20) Professor Gans claims that his calculations from fees charged on Google's ad server show fluctuations in price that are pertinent to a SSNIP analysis in his candidate ad server market:

> "Google DFP prices fluctuate. I present these price changes in Appendix D. Many of these changes are larger than a SSNIP. For example, in 2019 and 2020, total fees increased by [redacted]% and [redacted]% respectively. The per impression fee component decreased by [redacted]% in 2018 but increased by [redacted]% in 2020. However, during these periods when prices increased, we do not observe publishers adopting subscription models or building in-house ad servers."[64]

21) It is unclear whether Professor Gans views an increase in total fees or per unit impression fees as "larger than a SSNIP." If he views an increase in total fees as a SSNIP, he is incorrect. The changes in total fees to which he refers are actually changes in Google's total ad

[61] Gans Opening Report, at Section IV.C.2.

[62] More specifically, Professor Gans asserts that it would be "highly unlikely" that the New York Times would eliminate digital advertising from its strategy to generate revenue from content, that some publishers would not substitute toward a paywall revenue model, and that it would be costly to develop an in-house ad server. (Gans Opening Report, at ¶¶158-160). Professor Gans did not demonstrate any of his assertions through data analysis or documentary support.

[63] Gans Rebuttal Report, at ¶123. ("In addition, Google DFP prices fluctuate. I present these price changes in Appendix D.").

[64] Gans Rebuttal Report, at ¶123.

server revenue, which could increase for reasons completely unrelated to changes in the prices charged publishers (e.g., more publishers using DFP, existing customers attracting more users and having more impressions to monetize). Thus, his claim that increases in total fees of [redacted] percent and [redacted] are "larger than a SSNIP" is incorrect.[65]

22) If Professor Gans views the [redacted] percent increase in per impression fees[66] as "larger than a SSNIP," he is also incorrect because he has not demonstrated that the price increase was profitable. The application of a SSNIP in the HMT aims to define the relevant antitrust product market by asking whether a hypothetical, profit-maximizing monopolist controlling all of the products in a candidate market could *profitably* impose a small but significant, non-transitory increase in price on customers in the candidate relevant market.[67] Professor Gans fails to demonstrate that any such SSNIP is profitable. As shown in Exhibit 2 (which reproduces Professor Gans' Rebuttal Report Table 14 from which he bases his ad server SSNIP calculations) the [redacted] percent price increase results in a [redacted] percent *reduction* in total fees collected. This reduction in total fees may result in lower profits,[68] in which case his candidate ad server market fails the HMT (i.e., even a SSNIP less than 5 percent is unprofitable) and his market is defined too narrowly.[69]

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[65] The U.S. Merger Guidelines describe a SSNIP of 5 percent as the level that agencies often consider. (*See, e.g.*, Department of Justice & Federal Trade Commission, *Merger Guidelines*, 2023, at p. 43).

[66] Professor Gans attributes the [redacted] percent increase to 2020 in the text of his report. Gans Rebuttal Report, at ¶123. ("The per impression fee component decreased by [redacted]% in 2018 but increased by [redacted]% in 2020."). However, Appendix D, to which he refers as his support, indicates that the price change he calculates in 2020 is a decrease of [redacted] percent and that the price change he calculates in 2021 is an increase of [redacted] percent. I note that, consistent with the declining ad server prices I describe in the Baye First Report, Professor Gans finds year-over-year decreases in average per unit ad server fees every year except for 2021. *See* Baye First Report, at Exhibit 4.

[67] Department of Justice & Federal Trade Commission, *Merger Guidelines*, 2023, at pp. 41-42.

[68] Whether profits rise or fall depends on the level of marginal costs, which Professor Gans does not analyze. Therefore, his analysis does not, and cannot demonstrate his putative SSNIP is profitable. As I noted in the Baye First Report, if marginal costs are small, a SSNIP that reduces total revenue will result in lower profits. (Baye First Report, at ¶191, fn. 209).

[69] Because Professor Gans finds an increase in DFP average fees in 2021 and finds decreases in fees all other years he examines, his opinions concerning a SSNIP could only be applied to 2021. However, even in 2021 his application of a SSNIP is inappropriate, as I explain in more detail below.

Exhibit 2

[redacted]

23) Although Professor Gans' own logic would suggest that his ad server market is defined too narrowly, his application of the SSNIP test is flawed for several reasons:

a. Professor Gans' analysis does not establish the appropriate level of a SSNIP.[70]

b. Professor Gans' analysis does not establish the appropriate benchmark—i.e., the competitive price—for a SSNIP.[71] Nor does he establish that any of the prices he considers were at, above, or below the competitive level.

c. Professor Gans' analysis assumes that any firm that raises its price is a monopolist. This assumption is inconsistent with economic logic, as firms in competitive

[70] As I indicated in the Baye First Report, the typical price increase considered for a SSNIP is 5 percent. *See* Baye First Report, at ¶190, fn. 208.

[71] As I indicated in the Baye First Report, the SSNIP is applied to prices at competitive levels. *See, e.g.,* Baye First Report, at ¶¶227, 185. In his Opening Report, Professor Gans also characterized that SSNIP is being applied to prices at the competitive level, but never demonstrated a SSNIP in his candidate markets. Gans Opening Report, at ¶157. ("Based on my application of the HMT or hypothetical monopolist test, a small increase in the price of publisher ad servers above competitive levels would not result in significant substitution by open web display publishers to other products. In response to an increase in price, publishers have two potential options.").

markets routinely adjust prices—both up and down—in response to changes in supply or demand conditions.[72]

d. Professor Gans does not correctly analyze the data from which he calculates Google ad server revenue and prices. If one does not properly measure the prices that customers pay, then one cannot properly evaluate how they respond to a price increase. Professor Gans' calculation of DFP revenue,[73] and impressions served by DFP[74] are incorrect. Therefore, the prices he used to conduct his SSNIP are also incorrect.[75]

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[72] Professor Gans' interpretation is also inconsistent with the appropriate implementation of the HMT, which asks whether a hypothetical monopolist of a candidate product market could profitably implement a SSNIP *above competitive levels*—not whether any firm in that market has profitably raised prices in the past. (Department of Justice & Federal Trade Commission, *Merger Guidelines*, 2023, at pp. 41-42).

[73] For example, as I noted in the Baye First Report, Google generally waives DFP ad serving fees for ads transacted through AdX. (*See, e.g.,* Baye First Report, at ¶143, fn. 82). However, Professor Gans criticizes my calculations because they account for the actual prices that publishers pay accounting for the waived impression fees. (*See, e.g.,* Gans Rebuttal Report, at ¶515, fn. 818. "Professor Baye does not account for the fact that the discount fee, which is always negative, represent [sic] the dollar amount of the fees waived for a set of units and should not be subtracted from the total fees.").

Professor Gans' methodology also ignores other adjustments to the amounts that publishers pay for serving ads through DFP. For example, by ignoring the COVID-19 fee waivers provided to publishers, his methodology includes dollar amounts of fees, and can identify publishers as "paying customers," when a customer actually pays nothing at all to Google. (*See* Jason Washing, "Fee relief to support our news partners during COVID-19," Google The Keyword, April 17, 2020, available at: https://blog.google/outreach-initiatives/google-news-initiative/supporting-business-our-news-partners-during-covid-19/).

[74] Professor Gans sums together impression counts across line items even when doing so double-counts impressions. For example, Professor Gans' counts of DFP impressions include the impressions from line items that reflect all served impressions and then counts AdX impressions again from line items that indicate how many of these impressions are waived of fees and he counts impressions again from line items that indicate the number of impressions for which the publisher used ad server optimizations.

The production letter for the DFP fee data that Professor Gans relies upon specifies that these impressions waived of fees appear as positive numbers in the billed_units field. *See* Gans Rebuttal Report, at ¶515, fn. 818*; see also* "2024.02.15 Letter from D. Pearl to W. Noss and Z. DeRose," (February 15, 2024). ("Observations where fee_type is equal to "Discount_Fee" indicate units that are waived of fees… the volume of units waived of fees is indicated as a positive number of units in the field billed_units.").

Professor Gans' double-counting of impressions also impacts the calculations he presents in his Table 12. The volume of impressions per customer from 2014 to 2018 is considerably smaller than what Professor Gans reports in Table 12 of his Rebuttal Report. Figure 6 shows the corrected calculations for his Table 12, also correcting his count of publishers, described in more detail below.

[75] For example, Professor Gans calculates DFP fee revenue (or amounts paid by DFP customers) by excluding records in the data that completely reverse charges to customers for some or all of the impressions they serve. In the DFP fee data that Professor Gans utilizes (DOJ RFP 57 DFP Fees Data), he treats such AdX impressions that are waived of fees as amounts paid by

B. Professor Gans' New Ad Server Price Discrimination Analyses

24) Professor Gans also expresses new opinions concerning price discrimination in relation to Google's ad server fees and presents new data analyses of ad server fees which he interprets as supporting price discrimination.[76]

25) Professor Gans asserts that "Google has developed a complicated fee structure for use of their DFP ad server. The fee is constructed with multiple levels of price discrimination." As support for his opinion, Professor Gans refers to his Rebuttal Report Tables 4 and 11 which he describes as the average monthly DFP fee by fee type.[77] Taking his calculations in these tables as given, the fact that different customers utilize different mixes of Google services[78] does not amount to price discrimination. Professor Gans has provided no evidence that different customers pay different prices for a given type or level of service. Moreover, the numbers that Professor Gans presents in his Rebuttal Report Tables 4 and 11 are, in some instances, miscalculated by an order of magnitude, owing to errors in his computer code. Among other errors, instead of calculating the "average monthly fee per customer," Professor Gans computes the total revenue for each fee type over a nine-year period and divides this by the number of publishers who are associated with the

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customers and as Google revenue even though the customer is not charged, and Google does not collect the revenue. Specifically, in the DFP fee data, the impressions that are waived of fees are recorded under line items labeled with a fee_type of "Discount_Fee" and other fields, such as fee_subtype, provide additional context on the nature of these records. These discount line items appear with a negative billed amount and a positive number of billed units. In other words, these records reverse amounts indicated on other line items and indicate the number of impressions to which the reversal applies.

To illustrate how records appear in these data, consider a publisher that pays $16.70 in DFP ad serving fees and who ran 120 million impressions through DFP. The system that Professor Gans uses for his calculations could be used to show that the publisher actually incurred serving fees on only 1 million impressions (which, according to the DFP rate card would be charged at a rate of $0.0167 per thousand impressions), served 29 million AdX impressions that were waived of fees, and received 90 million standard ads also waived of fees, but that Professor Gans' methodology would calculate fees of $501 for the publisher and attribute a total of 59 million impressions to the publisher.

[76] Gans Rebuttal Report, at ¶¶119-124, 132, Tables 4-5.

[77] Gans Rebuttal Report, at Tables 4 and 11.

[78] For example, some publishers utilize Google's service to access log-level data from Bidding Data Transfer files (and, thus, are charged Data Transfer Fees) while others do not utilize these services (and, thus, are not charged).

fee type at any point in that period.[79] For instance, his Table 4 states that the average paying DFP customer pays [redacted] dollars per month for ad serving, when the actual number is [redacted].[80]

26) Professor Gans also presents a new analysis of the share of publishers that pay non-zero ad serving fees in his Rebuttal Report Tables 5 and 13; however, his calculations undercount the number of publishers who use DFP for free before 2020. In my Opening Report, I present data showing that from January 2020 to June 2023, [redacted] percent of DFP publishers paid no ad server fees.[81] My analysis is limited to the 2020 to 2023 period, because, prior to 2020, Google did not record fee data for publishers who used DFP for free. Professor Gans acknowledges this in his Rebuttal Report,[82] and he conducts analysis elsewhere that includes information about all publishers (those that do and do not pay to use DFP), but fails to do so when creating Rebuttal Report Tables 5 and 13. I correct Professor Gans' calculations by using data that include all publishers. I find that the share of publishers paying for DFP was [redacted] from 2014 through 2022.[83]

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[79] The critical error in Professor Gans' Rebuttal Report Tables 4 and 11 is that he divides total fees by the number of unique customers per fee type instead of the number of unique customer months per fee type. To illustrate the error in Professor Gans' calculation, suppose there are two paying customers for DFP. Customer A used DFP for 12 months and was charged $100 each month and Customer B used DFP for 3 months and was charged $200 each month. Professor Gans' Table 4 would present the average monthly payments per customer as $900 [= (12*$100 + 3*$200) / 2 customers], which in reality is an average of the aggregate fees paid by Customer A and Customer B [=($1200 + $ 600) / 2 customers]. The correction in my Figure 4 merely presents the number Professor Gans claims to show for paying customers. That is, the average monthly payment per customer is $120 [= (12*$100 + 3*$200) / (12 months + 3 months)].

I also note that Professor Gans claims that "'pub_service_country_code' is restricted to 'US'" for Tables 4, 5, 11, 12, 13, and 14. (Gans Rebuttal Report, at fn. 157, 167, 814, 816, 821-822). However, the field he actually uses is "pub_billing_country_code".

[80] *See* Figure 4. This calculation of standard ad serving fees accounts for reversed charges on impressions that are waived of fees, such as AdX impressions.

In Figure 4, I replicate Professor Gans' calculation and present a corrected calculation that shows an average monthly payment had Professor Gans corrected the error.

[81] Baye First Report, at Figure 45.

[82] Gans Rebuttal Report, at ¶514. ("My review of the data shows that the set of publishers in the data changed substantially between 2017 and 2018 and again between 2018 and 2019 with many smaller publishers with monthly impressions (proxied by billed units) entering the sample[.]").

[83] *See* Figure 5. Specifically, I utilize publisher counts from MDL 243 AdX, AdSense Backfill, and DFP Reservations to generate a count of publishers using DFP using conditions that reflect Professor Gans' calculations of DFP Fees data. These are

This means that Professor Gans' analyses on the share of publishers paying for DFP services—and the opinions based on those analyses—are flawed and unreliable.[84]

27) Finally, Professor Gans asserts that "because the ad server fee is above competitive levels at present, if subscription models or in house ad servers were reasonable substitutes, I expect to see a great deal of publishers adopting these options when prevailing prices change as a result of the Cellophane Fallacy. The evidence does not show such adoptions."[85] However, Professor Gans has not presented any evidence that Google's "ad server fee is above competitive levels."[86]

V. PROFESSOR GANS' NEW REGRESSION MODELS OF THE FACEBOOK BOYCOTT

28) In his Rebuttal Report, Professor Gans has performed a new econometric analysis which purportedly "summarizes statistical conclusions" about the Facebook Boycott.[87] Professor Gans introduces two econometric models (A and B) that compare display ad spend for 21 Google Ads advertisers during the 6-month Facebook Boycott period (July 2020 – December 2020) to display ad spend during a 30-month benchmark period (January 2019 – June 2020 and January

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the same data sources that Professor Gans utilizes in his Rebuttal Report Figure 40 in which he categorizes each DFP publisher as using AdX or not using AdX.

Additionally, Professor Gans claims that when defining a non-paying customer, "the discount fee, which is always negative, represents the dollar amount of the fees waived for a set of units and should not be subtracted from the total fees." (Gans Rebuttal Report, at ¶515, fn 818). As I indicated above, Professor Gans' assertion does not make economic sense. Under Professor Gans' methodology, a publisher that is charged $100 that receives a waiver of $100, would be classified as a paying customer that paid $100 rather than a non-paying customer that paid $0. In reality, the net amount paid by the publisher in this instance and the amount pocketed by Google are both zero dollars.

[84] For similar reasons, the new data analysis that Professor Gans provides in his Rebuttal Report Table 12 is also flawed. I correct this error in Figure 6. Therefore, his conclusion that "the set of publishers in the data changed substantially between 2017 and 2018 and again between 2018 and 2019 with many smaller publishers with monthly impressions (proxied by billed units) entering the sample" is an artifact of this error, rather than an actual change in the composition of publishers using DFP. (Gans Rebuttal Report, at ¶514).

[85] Gans Rebuttal Report, at ¶124.

[86] Ad serving fees on DFP have decreased since January 2014. See Baye First Report, at ¶292, Exhibit 4, Figures 45, 51.

[87] Gans Rebuttal Report, at ¶429.

2021 – December 2021) purportedly free of the effects of the Facebook Boycott.[88] Across the two models, Professor Gans "find[s] no significant effect of the boycott on the spending of selected advertisers on display ads."[89]

29) Professor Gans' econometric analysis is flawed both in methodology and execution.

30) First, contrary to the general principle that a larger sample size may improve statistical precision,[90] [redacted].[91] Specifically, Professor Gans has applied the following three filters without justification: (1) [redacted];[92] (2) [redacted].

31) Professor Gans does not state clearly why he applies the first data filter in his regression analysis, but it appears that he does so to "avoid the substitution pattern being driven by the composition change of firms."[93] However, Professor Gans ignores the role of advertiser

[88] Gans Rebuttal Report, at ¶¶429-432; Gans Rebuttal Report Backup Materials, folder "Facebook Boycott Analysis". In model A, Professor Gans normalizes the display ad spend by dividing it by its initial value in January 2019; in model B, he uses the logarithm of the display ad spend. (Gans Rebuttal Report, at ¶431). Professor Gans has included an indicator variable for the period July 2020 through December 2020 that is intended to provide a quantitative measure of the effect of the Facebook Boycott on Google Ads display ad spend across the selected group of Google Ads advertisers. (Gans Rebuttal Report, at ¶430). In the regression equation Professor Gans writes in his Rebuttal Report, he does not include the coefficient on this indicator variable. Professor Gans has also included controls which purportedly account for "the pre-existing trend in the growth of display ad spend as well as seasonality in the data" and "advertiser specific characteristics." (Gans Rebuttal Report, at ¶430).

[89] Gans Rebuttal Report, at ¶432.

[90] *See, e.g.,* Jeffrey Wooldridge, *Introductory Econometrics: A Modern Approach*, 4th Edition, South-Western Cengage Learning, 2009, at p. 175. ("When we combine these facts, we find that [the variance of the OLS estimator] shrinks to zero at the rate of 1/n; this is why larger sample sizes are better.").

[91] *See* Figure 7.

[92] *See* Figure 8.

[93] Gans Rebuttal Report, at ¶421. Professor Gans makes that statement about Figure 22 in his Rebuttal Report.

fixed effects, which are employed in his regression analysis, in controlling for any composition change of firms over time.[94] Specifically, his two regression models control for a linear time trend, month fixed effects, and advertiser fixed effects.[95] As a matter of econometrics, in a wide range of applications, the use of fixed effects in a regression model allows consistent estimation of the parameters in unbalanced panel data[96]—i.e., datasets that do not have time-series of equal length for all entities (e.g., advertisers).[97] Professor Gans provides no reason as to why, despite having fixed effects in his model, it is necessary to drop nearly 14 percent of the observations.[98] Dropping observations generally comes at the expense of precision.[99] For example, [redacted], which means Professor Gans censors the responses of

[94] *See* Figure 7.

[95] In general, fixed effect variables are a set of indicator variables, one for each possible value of a category variable. Advertiser fixed effects capture advertiser characteristics that are not measured in the available data, but that affect the level of their ad spend in the same way over time. Heuristically, these fixed effects are akin to estimating advertiser-specific intercepts that allow the estimated average ad spend curve to shift up and down for each advertiser. For instance, if advertiser A spends on average three times what advertiser B spends, this will be reflected in the estimates of the fixed effects. As another example, if there are seasonality considerations (e.g., ad spend is consistently higher in December than in other months), this will be reflected in the estimates of the monthly fixed effects. *See, e.g.,* ABA Section of Antitrust Law, *Econometrics*, 2nd Edition, ABA Publishing, 2014, at p. 353. ("In general, a fixed effect in a regression model will capture unexplained differences among groups of observations. A customer-fixed effect, for example, will capture the extent to which different customers paid different prices, even after controlling for other observable factors that might also affect prices.").

[96] Professor Gans' insistence on a balanced panel (each advertiser having exactly 36 observations) makes no sense because he then creates an unbalanced panel through his second and third filters arbitrarily dropping records. As a matter of logic, changing the order of his filters would result in him dropping some of the 21 advertisers he considers in his regression analysis.

[97] *See* Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach,* 4th Edition, South-Western Cengage Learning, 2009, pp. 488-489. ("Some panel data sets, especially on individuals or firms, have missing years for at least some cross-sectional units in the sample. In this case, we call the data set an unbalanced panel. The mechanics of fixed effects estimation with an unbalanced panel are not much more difficult than with a balanced panel. … The question is: If we apply fixed effects to the unbalanced panel, when will the estimators be unbiased (or at least consistent)? If the reason a firm leaves the sample (called attrition) is correlated with the idiosyncratic error—those unobserved factors that change over time and affect profits—then the resulting sample section problem … can cause biased estimators… Nevertheless, one useful thing about a fixed effects analysis is that it does allow attrition to be correlated with ai, the unobserved effect. The idea is that, with the initial sampling, some units are more likely to drop out of the survey, and this is captured by ai.").

[98] *See* Figure 7.

[99] *See, e.g.,* Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach*, 4th Edition, South-Western Cengage Learning, 2009, at p. 175. ("When we combine these facts, we find that [the variance of the OLS estimator] shrinks to zero at the rate of 1/n; this is why larger sample sizes are better.").

[redacted] to the Facebook Boycott despite his fixed effect approach being suited to their inclusion in his analysis.[100]

32) Professor Gans has not provided any explanation why he applies the second and third data filters. Professor Gans' second filter excludes all of an advertiser's ad spend in a month if the advertiser's spend did not include at least some ad spend through AdX, but this does not make economic sense because the outcome variable in his regression models is all open web display ad spend—not ad spend through AdX alone. Professor Gans' third filter excludes all of an advertiser's ad spend in a month where an advertiser significantly increased its open web display spend relative to other months.[101] This does not make economic sense because it risks excluding observations for advertisers whose open web display ad spend was most affected by the Boycott.[102] As noted earlier, there is a "cost" of losing observations and Professor Gans has failed to explain any potential upside of his approach.[103]

33) Second, Professor Gans' regression models impose the assumption that any effects of the Facebook Boycott on Google Ads advertisers' spend is restricted only to the six-month window that he attributes to the Boycott (July 2020 through December 2020), ignoring any potential longer-

[100] *See* Figure 8.

[101] For example, if an advertiser had $100 on Google Ads open web display ad spend in January 2019 and, owing to the Facebook Boycott, spent $5,000 in July 2020, Professor Gans' third filter would exclude the advertiser's ad spend in July 2020.

[102] Professor Gans' first and second filters also create this risk of eliminating information about substitution. An advertiser exclusively using Facebook before the boycott who begins buying open web display ads after the boycott would be entirely dropped from Professor Gans' regression analysis.

[103] Overall, Professor Gans' choice to look at a subset of the data effectively lowers variation and can distort how Google Ads advertisers adjusted their advertising spending in response to the Facebook Boycott. As such, his regression results can be used to speciously support a conclusion that there is no substitution when, in fact, there may be.

lasting effects that the Facebook Boycott might have on advertisers' ad spending choices in 2021.[104]

34) As shown below, making simple adjustments to his econometric analysis results in the estimated Facebook Boycott impact becoming statistically significant,[105] undermining Professor Gans' opinion that substitution from social ads to display ads is not likely.[106]

A. Professor Gans' Regression Model Imposes the Assumption That There Was No Longer-Term Impact on Ad Spend Following the Boycott

35) Professor Gans' model assumes that, exactly six months after the Facebook Boycott began, any ad spend that shifted from social media to the open web immediately shifted back. A more generalized model that makes no predetermined judgement about the change to ad spend after the Facebook Boycott can be implemented by merely adding an indicator variable for the period of time following the Facebook Boycott.[107]

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[104] Thus, by design, his regression fits data for the time period 2019 through 2021, assuming that any increase in display ad spend observed during his boycott window (July 2020 through December 2020) must revert after the window (except for increases due to the linear time trend that Professor Gans includes in his regression models). However, if the boycott did have longer-term effects on ad spend, the period of time he uses as his baseline to test for the increase would be contaminated by the effects of the boycott. As a result, Professor Gans would be less likely to find a significant effect when there may be, in fact, an effect. Professor Gans does not provide support for his assumed absence of longer-term effects in 2021 from the boycott.

[105] Statistically significant refers to being able to reject a stated "null hypothesis," essentially declaring that the result is convincing enough to overturn the previously stated explanation of a statistical phenomenon. (*See* Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach,* 4th Edition, South-Western Cengage Learning, 2009, pp. 120-128). In the present analysis, the "null hypothesis" is that the Facebook Boycott does not have any impact on the selected Google Ads advertisers' display ad spending. If the estimate of the coefficient of the Facebook Boycott indicator variable is statistically significant, it follows that the "null hypothesis" should be rejected, and the econometric evidence should be considered evidence that an impact exists.

[106] The adjustments should not be construed as an endorsement of Professor Gans' models—i.e., as an opinion that the models would be correct but for these modifications. Rather, the illustrations just show how Professor Gans' own models fail to support his conclusion after minor adjustments.

[107] In employing this methodology, and contrary to what Professor Gans has done, I do not assume anything about the impact of the Facebook Boycott on display ad spending during 2021. Rather, my econometric analysis tests whether and, if so, by what amount, display ad spending was higher (or lower) than it would have been but for the Facebook Boycott.

36) After adding an indicator variable for the period of time following the Facebook Boycott and removing the data filters, a variety of regression models and specifications broadly support a conclusion that the Facebook Boycott resulted in substitution toward open web display ads—contrary to Professor Gans' conclusion.[108] For model A, the coefficient of the Facebook Boycott indicator variable is [redacted] when Professor Gans' first data filter is removed, and [redacted] when all data filters are removed (the former is statistically significant at the ten percent level).[109] The coefficient of the long-term Facebook Boycott indicator variable (i.e., the variable that indicates whether a given display ad spend observation falls inside 2021) is [redacted] when Professor Gans' first data filter is removed, and [redacted] when all filters are removed (both estimates are statistically significant at the one percent level).[110] For model B, the coefficient of the Facebook Boycott indicator variable is [redacted] when Professor Gans' first data filter is removed, and [redacted] when all data filters are removed (both estimates are statistically significant at the one percent level).[111] The coefficient of the long-term Facebook Boycott indicator variable is [redacted] when Professor Gans'

[108] As explained in the Baye First Report, the FB boycott fails as a natural experiment because of non-random selection. See Baye First Report, at ¶260.

[109] *See* Figure 9. Here, this means that, according to my adjustment to Professor Gans' regression model A, the Facebook Boycott led to an increase of [redacted] percentage points in the normalized display ad spend in the boycott period relative to the period January 2019 – June 2020 in the former case, and in the latter case it did not have a statistically significant impact on display ad spend from July 2020 through December 2020, holding all else equal.

[110] *See* Figure 9. In the former case, the Facebook Boycott led to an increase of [redacted] percentage points in the normalized display ad spend from January 2021 through December 2021 relative to January 2019 through June 2020, holding all else equal. In the latter case, the Facebook Boycott led to an increase of [redacted] percentage points in the normalized display ad spend from January 2021 through December 2021 relative to January 2019 through June 2020, holding all else equal.

[111] *See* Figure 10. The Facebook Boycott led to a percentage increase of [redacted] percent in the former case and [redacted] percent in the latter case. (The percentage impact is calculated based on the estimated coefficient as: exp(estimate - (0.5 *std. error^2)) - 1). (*See* Peter Kennedy, "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations," *American Economic Review*, Vol. 71, 1981, p. 801, at p. 801).

first data filter is removed, and [redacted] when all filters are removed (both estimates are statistically significant at the one percent level).[112]

37) I note that the specifications in model B offer greater explanatory power (explaining about 60 percent of the variation in ad spend compared with at most 40 percent in model A). Additionally, the model B specifications provide for a standard, well-known interpretation of the coefficients,[113] and indicate statistically and economically significant increases in open web ad spend as a result of the Boycott.

B. Professor Gans' Estimates of the Boycott's Impact Are Driven by Ad Spend in 2021

38) The above conclusion that the Facebook Boycott resulted in statistically significant increases in open web display ad spend is robust to alternative ways of modeling the impact of the Facebook Boycott. The failure of Professor Gans' regression model to control for a long-term impact of the Facebook Boycott can also be shown by estimating his regression models after removing data from 2021. If there were not an increase in display ad spend during the second half of 2020, as estimated by Professor Gans' regression analysis that uses 2019-2021 data,[114] one should not see a substantially different measured impact based on a regression analysis that uses 2019 and 2020 data.

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[112] *See* Figure 10. The Facebook Boycott led to a percentage increase of [redacted] percent in the former case and [redacted] percent in the latter case. (The percentage impact is calculated based on the estimated coefficient as: exp(estimate - (0.5 *std. error^2)) - 1). (*See* Peter Kennedy, "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations," *American Economic Review*, Vol. 71, 1981, p. 801, at p. 801).

[113] The fact that Professor Gans has normalized the data for each advertiser individually before conducting his regression analysis makes it difficult to ascertain whether the magnitude of the coefficients in his model A are economically significant.

[114] Professor Gans says, "The dataset is monthly and spans from January 2019 to January 2021." (Gans Rebuttal Report, at ¶430). However, a review of Professor Gans' backup files shows that the data inputted into his regression models spans from January 2019 to December 2021. (Gans Rebuttal Report Backup Materials, folder "Facebook Boycott Analysis").

39) I estimated Professor Gans' regression model, with just two modifications: removal of his data filters and removal of the observations for the period January 2021 through December 2021. This sensitivity analysis counters Professor Gans' opinion about the non-existence of impact of the Facebook Boycott.[115] For model A, the coefficient of the Facebook Boycott indicator variable is [redacted] when Professor Gans' first data filter is removed, and [redacted] when all data filters are removed (the former is statistically significant at the five percent level, the latter is significant at the ten percent level).[116] For model B, the coefficient of the Facebook Boycott indicator variable is [redacted] when Professor Gans' first data filter is removed, and [redacted] when all data filters are removed (both estimates are statistically significant at the five percent level).[117]

40) Separately, in his Rebuttal Report, Professor Gans introduces an additional analysis, looking at "aggregated ad spend on DV360 for these 12 firms."[118] He concludes, "for both Google Ads and DV360, it is evident that there was no significant substitution between social media ads and display ads."[119] Professor Gans has not conducted any statistical analysis on DV360 and, therefore, he has failed to scientifically establish his conclusion that "there was no significant

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[115] The fact that the removal of observations from 2021 overturns Professor Gans' estimation results about the impact of the Facebook Boycott on Google Ads advertisers' display ad spend in 2020 indicates that his initial models suffer from various flaws. If Professor Gans' models were correctly specified (they are not), the estimates of the coefficient which purports to measure the shift in display ad spending from July 2020 through December 2020 would not depend so heavily on data from 2021. There is something in the 2021 data not controlled for by Professor Gans' regression model that significantly affects his results.

[116] *See* Figure 9. In the former case, the Facebook Boycott led to an increase of [redacted] percentage points in normalized display ad spend in July 2020 through December 2020 relative to January 2019 to June 2020. In the latter case, the Facebook Boycott led to an increase of [redacted] percentage points in normalized display ad spend in July 2020 through December 2020 relative to the period from January 2019 to June 2020.

[117] The Facebook Boycott led to a percentage increase of [redacted] percent in the former case and [redacted] percent in the latter case. (The percentage impact is calculated based on the estimated coefficient as: exp(estimate - (0.5 *std. error^2)) - 1). (*See* Peter Kennedy, "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations," *American Economic Review*, Vol. 71, 1981, p. 801, at p. 801).

[118] Gans Rebuttal Report, at ¶422.

[119] Gans Rebuttal Report, at ¶423.

substitution between social media ads and display ads."[120] Regardless, his opinion is at odds with Figure 23 in his Rebuttal Report, which shows that display ad spend on DV360 increased by more than [redacted] percent during the second half of 2020.[121]

VI. PROFESSOR GANS' NEW QUANTITATIVE ANALYSES OF UPR

41) In his Opening Report, Professor Gans concludes that "but for UPR [AdX impressions] would have been transacted through other exchanges and likely at higher prices."[122] However, Professor Gans' Rebuttal Report presents new analyses and opinions regarding the impact of UPR on publishers.[123] Based on his Rebuttal Report Figure 17, Professor Gans argues that "DFP publishers' AdX revenue did not increase and potentially declined as a result of UPR,"[124] and, based on his Rebuttal Report Figure 18, he asserts that "UPR had a significant negative effect on CPMs via AdX."[125] Based on his Rebuttal Report Figure 19, Professor Gans further asserts that "[t]he long-term reduction in AdX CPMs is particularly clear for large publishers, who are more likely to use sophisticated flooring mechanisms and, hence, were the biggest losers from the introduction of UPR."[126] In this section, I show that Professor Gans does not employ accepted scientific approaches to evaluate the impact of UPR, and I demonstrate that

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[120] Gans Rebuttal Report, at ¶423.

[121] According to Figure 23 in Professor Gans' Rebuttal Report, the aggregated DV360 ad spending on open web display of [redacted] firms participating in the Facebook Boycott jumped from around $[redacted] in July 2020 to close to $[redacted] in December 2020. By comparison, the increase from July 2021 to December 2021 is approximately [redacted] percent, going from about $[redacted] to $[redacted]. (Gans Rebuttal Report Backup Materials, folder "Facebook Boycott Analysis").

[122] Professor Gans further asserts that "[i]n the long run, as UPR dilutes publishers' ability to control the quality of their inventory, publishers' ability to monetize their business effectively is continuously reduced, exacerbating this effect." Professor Gans supports these conclusions based on empirical analysis of only one publisher: [redacted]. (Gans Opening Report, at ¶¶522–524, Figures 19, 20).

[123] In his Rebuttal Report, Professor Gans claims that "looking through the narrow lens of AdX revenue and not accounting for the confounding positive effect on revenue of the switch to the first price auction, publishers' revenue in AdX did not increase around the launch of UPR after accounting for the pre-existing trend." (Gans Rebuttal Report, at ¶346).

[124] Gans Rebuttal Report, at ¶346.

[125] Gans Rebuttal Report, at ¶347.

[126] Gans Rebuttal Report, at ¶347.

his conclusions lack any basis when one examines the statistical significance of his estimate of UPR's impact (which he reported in his analysis of the Facebook Boycott but omits from his UPR analysis).

42) As an initial matter, I note that Professor Gans' backup files reveal that he did not perform any statistical test to evaluate the statistical significance of his conclusions.[127] Although his methodology is inherently a statistical methodology (in that it recognizes the fitted curve is subject to statistical error),[128] Professor Gans does not produce the statistical standard errors (or, equivalently, the confidence intervals) associated with the coefficients he obtained from his "non-linear regressions."[129] Therefore, his backup materials do not support his conclusions that UPR impacted publishers because his analysis cannot evaluate the likelihood that the impact he claims to find is merely the product of chance.[130] In order to test Professor Gans' conclusions, I recover the statistical error associated with his estimates and I find that his conclusions are not supported

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[127] More specifically, Professor Gans implements two separate data-fitting methods—one before UPR and one after UPR—and utilizes the coefficients (or parameters) of the fitted quadratic forms to construct the smooth lines on his Figures 17, 18, and 19. A quadratic form is one in which the model is specified with three coefficients: an intercept (a), a slope that defines the linear relationship (b), and a squared slope that defines the curvature of the line (c). In a statistical model where a variable of interest y is fitted onto a quadratic model that depends upon time (as Professor Gans uses in his new UPR analyses), the relationship may be written as the following model: $y_t = a + bt + ct^2 + \varepsilon_t$ where ε_t is the statistical error from the model.

[128] *See, e.g.,* David Kaye and David Freedman, "Reference Guide on Statistics," in *Reference Manual on Scientific Evidence*, 3rd Edition, 2011, at p. 240, fn. 83. ("Random error is also called sampling error, chance error, or statistical error. Econometricians use the parallel concept of random disturbance terms.").

[129] Professor Gans' backup file "UPR Impact on DFP – DRX data.ipynb" specifies the following before his estimation: "Fit the data using non-linear regressions."

Professor Gans uses the command np.polyfit() to obtain coefficients for the fitted quadratic form, and omits the parameter 'cov' that report the estimated coefficients' covariance matrix. By default, 'cov' parameter is set up to False (*See* NumPy Reference, "numpy.polyfit," available at: https://numpy.org/doc/stable/reference/generated/numpy.polyfit.html. Accessed October 1, 2024). Professor Gans' modeling approach, referred to as Polynomial Approximation via Least Squares (*See* Kenneth Judd, *Numerical Methods in Economics*, 1st Edition, MIT Press, 1998) in the academic literature, finds the best second-order polynomial that approximates the data so that "the fitted lines follow a quadratic form, with months corresponding to the UPR ramp up stage excluded from the fitting process." (*See* Gans Rebuttal Report, at Figure 18, fn. 600). Because of the lack of standard errors, this modeling approach does not allow for a proper analysis of statistical significance of the corresponding coefficients.

[130] *See, e.g.,* David Kaye and David Freedman, "Reference Guide on Statistics," in *Reference Manual on Scientific Evidence*, 3rd Edition, 2011, at p. 240. ("If a pattern in the data is the result of chance, it is likely to wash out when more data are collected. By applying the laws of probability, a statistician can assess the likelihood that random error will create spurious patterns of certain kinds. Such assessments are often viewed as essential when making inferences from data.").

by his UPR models.[131] As discussed in more detail below, standard, accepted statistical tests strongly reject Professor Gans' conclusions that UPR harmed publishers in general and large publishers in particular.

43) Professor Gans suggests that his analysis informs a "but-for" world in which Google had not implemented UPR.[132] However, he does not use his regression coefficients to actually estimate or even plot the "but-for" publisher revenue and CPMs on AdX that his model predicts. Professor Gans' descriptions of the "impact" of UPR refer simply to a comparison of two curves: the continuation of the pattern that his model estimates before UPR into the time period after UPR was implemented, compared to the curve he fits to actual data points after UPR was implemented. To illustrate, in Exhibit 3, I plot the but-for world implied by Professor Gans' regression analysis. Visually, this is the dashed red line, which represents the continuation of the solid red line before UPR he presented in his Rebuttal Report Figure 17 into the months that he analyzes after UPR. In Exhibit 4, I generate the analogous but-for world of publisher average CPM using the model Professor Gans implements in his Figure 18. In Exhibit 5, I compute the analogous but-for world for Professor Gans' analysis limited to what he calls "large publishers" for his Figure 19.

[131] Columns (b) and (d) in Figure 11 reproduce Professor Gans' polynomial fit coefficients as obtained directly from his backup files which generate the fitted lines in his Rebuttal Report Figures 17 and 18. Column (c) in Figure 11 demonstrates that the results from a statistical regression of publishers' AdX revenue on an intercept, time trend, and quadratic time trend recovers identical coefficient estimates as found in Professor Gans' Rebuttal Report Figure 17, along with the statistical error of each coefficient. Column (e) in Figure 11 demonstrates the same from a regression of the average AdX CPM as Professor Gans' Rebuttal Report Figure 18, with the statistical error from these estimates.

[132] "I show that DFP publishers' AdX revenue did not increase and potentially declined as a result of UPR. Again, this largely understated the publisher's revenue 'but-for' UPR because it is not possible to isolate UPR from the first-price auction launch." (Gans Rebuttal Report, at ¶346).

Exhibit 3

[redacted]

Notes: The same data limitations as applied by Professor Gans in Figures 17 and 18 of his Rebuttal Report have been applied here: "DRX Internal Stats data is used for this analysis. The column 'is_mobile_app_request' is filtered to be 'False' and the column 'is_youtube_inventory' is filtered to be 'False.' The data is aggregated at the 'gfp_network_id' and 'month' level, all rows with non-positive 'impressions' or negative 'publisher_gross_revenue_usd' are excluded. "Revenue" is derived from the column "publisher_gross_revenue_usd." (Gans Rebuttal Report, at Figure 17, fn. 597, Figure 18, fn. 600).

Source: Gans Rebuttal Report Backup Materials; DOJ RFP 57 DRX Internal Stats Data.

Exhibit 4

[redacted]

Notes: The same data limitations as applied by Professor Gans in Figures 17 and 18 of his Rebuttal Report have been applied here: "DRX Internal Stats data is used for this analysis. The column 'is_mobile_app_request' is filtered to be 'False' and the column 'is_youtube_inventory' is filtered to be 'False.' The data is aggregated at the 'gfp_network_id' and 'month' level, all rows with non-positive 'impressions' or negative 'publisher_gross_revenue_usd' are excluded. CPM is calculated as the ratio of "publisher_gross_revenue_usd" and "matched_impressions" (divided by 1000). Impressions are via AdX if the column "transaction_type" has the value "0" or "4," which represents "Open auction" and "First Look deals" (Gans Rebuttal Report, at Figure 17, fn. 597, Figure 18, fn. 600).

Source: Gans Rebuttal Report Backup Materials; DOJ RFP 57 DRX Internal Stats Data.

Exhibit 5

[redacted]

Notes: The same data limitations as applied by Professor Gans in Figure 19 of his Rebuttal Report have been applied here: "DRX Internal Stats data is used for this analysis. The column 'is_mobile_app_request' is filtered to be 'False' and the column 'is_youtube_inventory' is filtered to be 'False.' The data is aggregated at the 'gfp_network_id' and 'month' level, all rows with non-positive 'impressions' or negative 'publisher_gross_revenue_usd' are excluded. CPM is calculated as the ratio of "publisher_gross_revenue_usd" and "matched_impressions" (divided by 1000). Impressions are via AdX if the column "transaction_type" has the value "0" or "4," which represents "Open auction" and "First Look deals" A publisher is large if the column "gfp_product_segment_name" is "PREMIUM" or "PREMIUM_WHITELIST." (Gans Rebuttal Report, at Figure 17, fn. 597, Figure 18, fn. 600, Figure 19, fn. 601).

Source: Gans Rebuttal Report Backup Materials; DOJ RFP 57 DRX Internal Stats Data.

44) Professor Gans' simplistic approach to the but-for world reveals several flaws in his analysis of UPR's impact, undermining and sometimes even contradicting his conclusions. First, Exhibit 4 shows that Professor Gans' assertion that [redacted]"[133] does not comport with, and even cuts against, the predictions of his model.

[133] Gans Rebuttal Report, at ¶347.

Whereas his model predicts (the dashed red line)—based exclusively on data from before the implementation of UPR—that [redacted] actual outcomes (the green line) show that [redacted]. Thus, contrary to his opinion that UPR harmed publishers, Professor Gans' approach more plausibly suggests that UPR benefited publishers.[134] The same is true regarding Professor Gans' analysis of CPMs for "large publishers," as shown in Exhibit 5.

45) Second, the fitted curves for revenue before and after UPR (in Exhibit 3) are clearly subject to statistical error, as evidenced by the fact that the observed data points do not perfectly fall on his red and green solid lines. It could then be that any difference between the green (estimated post-UPR) and dashed (extension of pre-UPR) curve is just due to chance. I conduct the statistical analysis that Professor Gans omits, and the results demonstrate that the pattern of publisher revenue observed after UPR is not statistically distinguishable from his prediction of publisher revenue but for the implementation of UPR.[135] That is, Professor Gans' own quadratic

[134] Review of Professor Gans' backup files reveals that he also analyzes publishers' matched impressions via AdX using the same modeling approach as described above. Professor Gans does not present in his report the figure that his backup files create. I show Professor Gans' omitted result as Figure 12. Contrary to the claim in Professor Gans' Rebuttal Report that "Google's use of its ad server monopoly power to steer transactions to its ad exchange and ad buying tools is not competition on the merits," (Gans Rebuttal Report, at ¶341). Figure 13 suggests that in Professor Gans' simplistic but-for world, the estimated impression volume transacted through AdX absent UPR increases over time while publishers' impressions on AdX are relatively flat after UPR, and even tend to decline a year later. These results suggest that UPR did not result in AdX winning more impressions than it otherwise would have.

[135] In columns (b) and (c) from Figure 14, I present results from a single regression model where the dependent variable is publishers' AdX revenue and CPM in AdX, respectively. Column (d) in Figure 14 presents regression results where the dependent variable is publishers' matched impressions in AdX. These results include Professor Gans' quadratic model and interact his quadratic parameters with a UPR indicator. As a result, the slope, time trend, and squared time trend from Professor Gans' regression on data only after UPR are equal to the sum of the intercept and UPR indicator, the sum of the time trend and UPR time trend interaction, and the sum of the squared time trend and UPR interacted squared time trend, respectively. Because this single regression model nests the two separate fitting processes from Professor Gans' analysis, the regression results I present exactly recreate the point estimates from Professor Gans' baseline specification of a second-degree polynomial curve, before and after UPR. I note that for both specifications there is no statistically significant change in the intercept, the linear term or the quadratic term after the introduction of UPR. This is evidenced by the lack of statistical significance for the coefficients of UPR and UPR interacted with time and time squared (rows 4-6) in columns (b) and (c).

In his Rebuttal Report Figure 19, Professor Gans presents data to suggest that "the long-term reduction in AdX CPM is particularly clear for large publishers." (Gans Rebuttal Report, at ¶347). According to Professor Gans Rebuttal Report, at Figure

model provides no statistical evidence to support his claim that UPR harmed publisher revenue.[136] Similarly, the regression results reject Professor Gans' conclusion that "CPMs on AdX decreased overall, across all publishers, around the launch of UPR"[137] and also reject his conclusion that "[t]he long-term reduction in AdX CPMs is particularly clear for large publishers."[138]

46) Third, each plot of the data shows a large divergence in the overall trend that does not coincide with the implementation of UPR but, rather, with the COVID-19 shutdowns beginning in March 2020. The divergence is most notable in April and May of 2020 (I have encircled both months on each exhibit above), which appear as outliers in these plots. Professor Gans applies no statistical controls to his model other than his quadratic time trend. In doing so, he cannot disentangle the impact of UPR on publishers' AdX revenue and CPM from the potential impact of other omitted variables, such as the impact of the COVID-19 pandemic shutdowns on the supply and demand for display ads.[139] I implement a straightforward statistical model (in which Professor

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18, fn. 601, "a publisher is large if the column "gfp_product_segment_name" is "PREMIUM' or 'PREMIUM_WHITELIST.'" Review of DRX Production Letter (*See* GOOG-AT-MDL-009777293), suggests that the field can take on the following values "Values 0:UNKNOWN, 1 :SMALL_BUSINESS, 2:PREMIUM, 3:PREMIUM_WHITELIST, 4:YOUTUBE_XFP, and only applicable for GFP publishers." Professor Gans has not demonstrated that this criterion is a valid approach to classify publishers nor has he provided any support behind this definition.

[136] I also run regressions on Professor Gans' analysis of matched impressions, which appear in his backup materials but are not discussed in the text of his report. Figure 12 reproduces Professor Gans' plot of matched impressions from his Rebuttal Report backup materials. Figure 13 plots the but-for world implied by the quadratic model in his backup. The regression results, shown in column (d) of Figure 14, indicate that UPR did not increase AdX's impressions relative to what they would have been in Professor Gans' but-for world. Note that the negative interaction between UPR and squared time trend indicates that, if anything, UPR stemmed the growth of AdX impressions. The F-test indicates that these effects, which are displayed in Figure 13, are statistically significant.

[137] Gans Rebuttal Report, at ¶347. The regression on CPM shown in Figure 14 column (c) indicates that the impact of UPR is not statistically significant on the components of Professor Gans' quadratic model. The F-test indicates that the benefits of UPR displayed in Exhibit 4 are statistically significant.

[138] Gans Rebuttal Report, at ¶347. The regression on CPM for "large publishers" shown in Figure 15 column (c) indicates that the interacted intercept and squared trend are not statistically significant. If anything, Figure 15 shows that large publishers benefited from UPR because the coefficient on the UPR time trend interaction is positive and statistically significant at the 10 percent level. The F-test indicates that the benefits of UPR displayed in Figure 15 are statistically significant at the 1 percent level.

[139] It is well established in the econometrics literature that omitting relevant factors from the regression model could result in incorrect estimates for the coefficient of the variable of interest, misattributing the effect of the omitted factors to that variable. *See, e.g.,* Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach,* 4th Edition, South-Western Cengage Learning, 2009, p. 89.

Gans' model is a nested[140] special case) to test whether COVID-19 disturbances provide substantially greater explanatory power for the fluctuations in revenue, CPMs, and impressions than UPR. Standard statistical tests reject Professor Gans' conclusion that UPR harmed publishers, and demonstrate that the COVID-19 pandemic (which Professor Gans discusses in his report[141] but fails to control for in his regression analysis) is an important variable to include.[142] While the estimates of UPR's impact are not statistically different from zero, the COVID-19 pandemic had a negative and statistically significant effect on publishers' AdX revenue and CPMs, and a positive and statistically significant effect on publishers' matched impressions in AdX. That is, statistical tests on these models support COVID-19 explaining changes in publisher outcomes and provide no evidence that UPR does.[143]

47) To summarize, Professor Gans' new results fail to provide scientific evidence of a causal relationship between UPR and harm to publishers. The fact that his regression analysis is nested in a model that rejects his hypothesis that UPR harmed publishers in favor of the alternative that the effects he observes stem from the COVID-19 pandemic is strong evidence that the correlation he identifies is spurious.[144]

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[140] Nested hypothesis testing is an accepted technique for the validity of one regression model (e.g., Professor Gans' model) against an alternative (e.g., one that contains Professor Gans' model as a special case but also controls for other factors). As one popular econometrics textbook puts it, F-tests "allow us to test nested models: one model (the restricted model) is a special case of the other model (the unrestricted model)." (Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach,* 4th Edition, South-Western Cengage Learning, 2009, at p. 201).

[141] Gans Rebuttal Report, at ¶347, fn. 599.

[142] *See* Figure 16.

[143] Figure 16 and Figure 17 show through an F-test that the data statistically rejects the joint hypotheses that the COVID-19 pandemic coefficients are all equal to zero but fails to reject that the estimated UPR coefficients are, jointly, statistically different from zero.

[144] As Daniel Rubinfeld notes in his chapter of the Reference Manual on Scientific Evidence, "in making causal inferences, it is important to avoid spurious correlation. Spurious correlation arises when two variables are closely related but bear no causal relationship because they are both caused by a third, unexamined variable. For example, there might be a negative correlation

VII. PROFESSOR GANS' NEW QUANTITATIVE ANALYSIS OF THE ALLEGED "CONTRACTUAL TIE"

48) Professor Gans' Rebuttal Report presents new analysis of the alleged "contractual tie" through his calculation of the "[s]hare of DFP impressions from publishers who did not use AdX."[145] Based on this new analysis, Professor Gans asserts that "beginning with the tie in 2016 and continuing after, the number of impressions (the more important variable) sold by DFP publishers not using AdX drop [sic] sharply. By 2021, DFP publishers who did not use AdX were selling less than [redacted] percent of impressions in DFP."[146] Professor Gans also asserts that his new analysis shows that "the publishers that could generate profits for a competing ad server or new entrant are foreclosed by the Google tie. The data does show that most publishers would keep DFP and not switch to competitors absent the tie."[147] As discussed below, Professor Gans' conclusions are based on flawed analysis.

between the age of certain skilled employees of a computer company and their salaries. One should not conclude from this correlation that the employer has necessarily discriminated against the employees on the basis of their age. A third, unexamined variable, such as the level of the employees' technological skills, could explain differences in productivity and, consequently, differences in salary." (Daniel Rubinfeld, "Reference Guide on Multiple Regression," in *Reference Manual on Scientific Evidence*, 3rd Edition, 2011, at p. 309)

[145] Gans Rebuttal Report, at Figure 16.

[146] Gans Rebuttal Report, at ¶318.

[147] Gans Rebuttal Report, at ¶319.

49) Professor Gans' Rebuttal Report Figure 16 is based on erroneous calculations.[148] Exhibit 6 below shows that, when corrected,[149] the acceleration in the decline in 2016 shown in his Figure 16 disappears; instead, the decline continues at roughly the same rate before and after 2016.[150] Furthermore, Professor Gans' Rebuttal Report Figure 16 shows the share of impressions for a subset of publishers rather than the *number* of impressions—which he asserts to be "*the more important variable*."[151] Contrary to his assertions, Exhibit 6 below shows that there is no sharp

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[148] Professor Gans describes his Rebuttal Report Figure 16 as showing "the ratio of the following two impression counts in each year: (1) the number of impressions from DFP publishers who did not use AdX, and (2) the number of impressions in all three datasets" for each year from 2013 through 2021. However, due to an error in his code—he uses a command that, by default, computes averages across certain groups of impressions, rather than summing together impressions—the methodology that Professor Gans employs does not actually calculate the ratio he describes.

Professor Gans uses RFP 243 DFP Reservations data, AdX data, and AdSense Backfill data to produce Figure 16 of his Rebuttal Report. Gans Rebuttal Report, at Figure 16, fn. 536. ("RFP 243 DFP Reservations data, AdX data, and AdSense Backfill data are used for this analysis."). I also note that two of the three datasets Professor Gans uses only contain a partial year of data for 2013. The RFP 243 DFP Reservations data and AdX data only include observations for the last seven months of 2013. *See* Figure 18 which presents Professor Gans' calculation and the corrected version of his calculation at the monthly level.

Professor Gans limits the data to U.S. users and excludes AdX Direct impressions and non-positive impressions. Gans Rebuttal Report, at Figure 16, fn. 536. ("In these datasets, the column 'country_criteria_id' is filtered to be '2840,' which represents the US. In the AdX data, the column 'is_adx_direct' is filtered to be 'False.' Rows with non-positive impressions are excluded.").

Professor Gans defines "[a] DFP publisher who did not use AdX … when the column 'transaction_type_name' is not related to 'Open Auction' or 'First Look.'" (Gans Rebuttal Report, at Figure 16, fn. 536).

[149] In his code file [redacted]

His code is: [redacted] This means that if the parameter "aggfunc" is not specified in the code, the default is to use the mean, or average, to aggregate the data. Professor Gans then sums these averages, and then uses those summed values to calculate the share of DFP impressions from publishers who did not use AdX.

[150] One can see this more clearly in Figure 18, which displays these data at the monthly, rather than annual, level.

[151] "[B]eginning with the tie in 2016 and continuing after, the number of impressions (*the more important variable*) sold by DFP publishers not using AdX drop sharply." (Gans Rebuttal Report, at ¶318, emphasis added).

drop in the *number* of impressions around the time of the alleged tie.[152] In short, after correcting Professor Gans' code,[153] the sharp drop he attributes to the "contractual tie" in 2016 disappears and the data are consistent with trends observed before 2016. If anything, the data show that the alleged tie stemmed the decline in the number of impressions from publishers who did not use AdX.[154]

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[152] *See also* Figure 19 where the number of impressions is depicted using more granular, monthly data.

[153] I correct Professor Gans' code by [redacted], as described above. This correction applies to all years in the data. The size of the change from this correction has a small impact between 2013 and 2015 due to the structure of the data.

[154] *See* Figure 19.

Exhibit 6

[redacted]

Notes: The values from Professor Gans' Rebuttal Report Figure 16 are displayed as the red line. Due to an omission in one command line in his code, Professor Gans does not actually calculate the ratio he describes. Correcting this calculation to reflect Professor Gans' methodology results in the correct shares, displayed as the blue line.

Source: MDL RFP 243 DFP Reservations data; MDL RFP 243 AdX data; MDL RFP 243 AdSense Backfill data.

Mike Baye

Michael R. Baye
October 4, 2024

APPENDIX A. MATERIALS RELIED UPON

In preparing the Sur-Rebuttal Report, I relied upon all of the materials listed in Appendix II to my First Report, as well as the materials listed below.

Academic Literature and Published Books

ABA Section of Antitrust Law, *Econometrics*, 2nd Edition, ABA Publishing, 2014.

Daniel Rubinfeld, "Reference Guide on Multiple Regression," in *Reference Manual on Scientific Evidence*, 3rd Edition, 2011.

David Kaye and David Freedman, "Reference Guide on Statistics," in *Reference Manual on Scientific Evidence*, 3rd Edition, 2011.

Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach*, 4th Edition, South-Western Cengage Learning, 2009.

Kenneth Judd, *Numerical Methods in Economics*, 1st Edition, MIT Press, 1998.

Lars Stole, "Price Discrimination and Competition," in *Handbook of Industrial Organization Volume 3*, ed. Mark Armstrong and Robert Porter, 2007.

Michael R. Baye and Jeffrey T. Prince, *Managerial Economics and Business Strategy*, 10th Edition. McGraw-Hill, 2021.

Peter Kennedy, "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations," *American Economic Review*, Vol. 71, 1981, p. 801.

Case Law and Government Filings

Department of Justice & Federal Trade Commission, *Merger Guidelines*, 2023.

In the Matter of Marathon Petroleum Corporation, Trade Reg. Rep. P 17906 (C.C.H.), 2018 WL 5840959 (Oct. 25, 2018).

Data Production Letters

"2024.02.15 Letter from D. Pearl to W. Noss and Z. DeRose," (February 15, 2024).

"2023.04.17 Transmittal Letter re Data Production," (April 17, 2023).

Expert Reports

Expert Report of Michael R. Baye, August 6, 2024.

Expert Report of Joshua Gans, June 7, 2024.

Rebuttal Report of Joshua Gans, September 9, 2024.

Bates Stamped Documents

[redacted]

GOOG-AT-MDL-008842383.

GOOG-AT-MDL-009777293.

GOOG-DOJ-AT-00569936.

GOOG-NE-04732984.

Other Sources

Bidswitch, "Technology - A smart infrastructure for programmatic platforms," available at: https://www.bidswitch.com/technology/. Accessed September 24, 2024.

CDC, "COVID-19 Timeline," available at: https://www.cdc.gov/museum/timeline/covid19.html. Accessed September 24, 2024.

Google, "Supported display exchanges - Display & Video 360 Help," available at: https://support.google.com/displayvideo/table/3267029. Accessed September 16, 2024.

Jason Washing, "Fee relief to support our news partners during COVID-19," Google The Keyword, April 17, 2020, available at: https://blog.google/outreach-initiatives/google-news-initiative/supporting-business-our-news-partners-during-covid-19/.

NumPy Reference, "numpy.polyfit," available at: https://numpy.org/doc/stable/reference/generated/numpy.polyfit.html. Accessed October 1, 2024.

pandas, "pandas.pivot_table," available at: https://pandas.pydata.org/docs/reference/api/pandas.pivot_table.html. Accessed September 18, 2024.

Prebid, "Running Prebid.js without an ad server," available at: https://docs.prebid.org/dev-docs/examples/no-adserver.html. Accessed September 13, 2024.

Prebid, "What is Prebid.js?" available at: https://docs.prebid.org/prebid/prebidjs.html. Accessed September 16, 2024.

Sovrn, "Ad Tags in Ad Exchange," available at: https://knowledge.sovrn.com/kb/ad-tags-in-ad-exchange. Accessed September 17, 2024.

Sovrn, "How to Install Sovrn Ad Tags on a WordPress Site," available at: https://www.sovrn.com/blog/install-ad-tags-wordpress-site/. Accessed September 17, 2024.

APPENDIX B. FIGURES

[redacted]

[redacted]

[redacted]

[redacted]

Figure 4

[redacted]

Figure 5

[redacted]

Figure 6

[redacted]

Figure 7

[redacted]

Figure 8
Number of Ad Spend Observations for Advertisers Excluded by Professor Gans' Filter #1

[redacted]

Figure 9

[redacted]

Figure 10

[redacted]

[redacted]

Figure 12

[redacted]

Figure 13

[redacted]

Figure 14

[redacted]

Figure 15

[redacted]

Figure 16

[redacted]

Figure 17

[redacted]

Figure 18

[redacted]

Figure 19

[redacted]